Problem 1

$$\frac{\partial E}{\partial a_k} = -\sum_{n=1}^N \sum_{j=1}^K t_{nj} \frac{1}{y_j(\mathbf{x_n, w})} \frac{\partial y_j(\mathbf{x_n, w})}{\partial a_k} \text{ where } y_j = \frac{e^{a_j}}{\sum_{i=1}^K e^{a_i}}$$

$$(j = k) \frac{\partial y_j(\mathbf{x_n, w})}{\partial a_k} = \frac{e^{a_k} \sum_{i=1}^K e^{a_i} - e^{a_k} e^{a_k}}{\left[\sum_{i=1}^K e^{a_i}\right]^2} = y_k (1 - y_k)$$

$$(j \neq k) \frac{\partial y_j(\mathbf{x_n, w})}{\partial a_k} = -\frac{e^{a_k} e^{a_j}}{\left[\sum_{i=1}^K e^{a_i}\right]^2} = -y_k y_j$$

$$\text{let } \delta_{jk} = \begin{cases} 1 & \text{if } j = k \\ 0 & \text{otherwise} \end{cases}$$

$$\Rightarrow \frac{\partial E}{\partial a_k} = -\sum_{n=1}^N \sum_{j=1}^K t_{nk} \frac{1}{y_j} y_j (\delta_{jk} - y_k)$$

$$= \sum_{n=1}^N \sum_{j=1}^K t_{nj} (y_k - \delta_{jk})$$

$$\sum_{j=1}^K t_{nj} = 1 \Rightarrow \sum_{j=1}^K t_{nj} y_k = y_k \quad t_n \text{ is a one-of-K coding scheme.}$$

$$\sum_{j=1}^K t_{nj} \delta_{jk} = t_{nk} \delta_{kk} = t_{nk} \quad \delta_{jk} = 1 \text{ if } j = k \text{ and } \delta_{jk} = 0 \text{ otherwise.}$$

$$\text{Thus, } \frac{\partial E}{\partial a_k} = \sum_{n=1}^N y_k - t_{nk}$$

Problem 2

Designed a neural net that contained 10 units in its hidden layer, used a batch size of 10, a learning rate of 0.001, a tolerance of 0.1, and 1000 as the maximum number of iterations. Obtained a 99.5% accuracy on training data and 110% accuracy on the test data.

Neural Nets Implementation & XOR Problem

```
In [33]:
          import numpy as np
          import pickle
          import matplotlib.pyplot as plt
          from sklearn.model selection import train test split
In [14]:
          # Load xor toy dataset
          with open('xordata.pkl', 'rb') as f:
              data = pickle.load(f)
          X_train = data['X_train'] # 800 training data points with 2 features
          y_train = data['y_train'] # training binary labels {0,1}
          X test = data['X test']
          y_test = data['y_test']
In [15]:
          print(X_train.shape, y_train.shape)
          print(X_test.shape, y_test.shape)
         (800, 2) (800,)
         (200, 2)(200,)
In [16]:
          X_val,X_test,y_val,y_test=train_test_split(X_test,y_test,test_size=0.5)
In [7]:
          plt.scatter(X_train[:,0], X_train[:,1], s=40, c=y_train, cmap=plt.cm.Spectral)
Out[7]: <matplotlib.collections.PathCollection at 0x7fabf133ee80>
           4
           3
           2
           1
           0
          ^{-1}
          -2
          -3
              -3
```

Instructions:

Goal: implement from scratch brackprop to train a simple neural network and test it on a simple dataset.

• Implement brackprop to train a two-layer perceptron: an input layer, a hidden layer, and an output layer.

- The core of the code should include: a forward pass; a backward pass; weight updates.
- For input and output layers specify the number of nodes appropriate for the above problem.
- Randomly initialize the weights and biases of the network.
- For the hidden layer use ReLU as an activation function and for the output layer use logistic sigmoid.
- Use cross-entropy loss as the network's loss function and mini-batch SGD as the optimizer.
- Feel free to tune the network as you see fit (including number of units in the hidden layer, learning rate, batch size, number of epochs, etc).
- (Optional) You can use sklearn.inspection.DecisionBoundaryDisplay to visualize your decision boundary.
- Report the accuracy of the network on the train and test set. Remember to create and use a validation set for the training phase!

```
In [34]:
          def relu(x):
              return np.maximum(0,x)
          def relu derivative(x):
              return np.where(x>0,1,0)
          def sigmoid(x):
              return 1/(1+np.exp(-x))
          def sigmoid derivative(x):
              return sigmoid(x)*(1-sigmoid(x))
          class TwoLayerPerceptron:
              def init (self,input dim,hidden dim,learning rate=0.001,batch size=10,epd
                  self.learning rate=learning rate
                  self.epochs=epochs
                  self.batch_size=batch_size
                  self.tol=tol
                  self.W1,self.b1,self.W2,self.b2=self.initialize parameters(input dim,hid
              def initialize_parameters(self,input_dim,hidden_dim):
                  W1=np.random.randn(input dim,hidden dim)
                  b1=np.random.randn(hidden_dim)
                  W2=np.random.randn(hidden dim,1)
                  b2=np.random.randn(1)
                  return W1, b1, W2, b2
              def forward pass(self,X):
                  Z1=np.dot(X,self.W1)+self.b1
                  A1=np.apply along axis(relu,0,Z1)
                  Z2=np.dot(A1,self.W2)+self.b2
                  A2=sigmoid(Z2)
                  return Z1,A1,Z2,A2
              def backward_prop(self,X,y,Z1,A1,Z2,A2):
                  m=X.shape[0]
                  dA2=A2-np.reshape(y,(-1,1))
                  dZ2=dA2*sigmoid derivative(Z2)
                  dW2=(1/m)*np.dot(A1.T,dZ2)
```

```
db2=(1/m)*np.sum(dZ2)
                  dA1=np.dot(dZ2,self.W2.T)
                  dZ1=dA1*relu derivative(Z1)
                  dW1=(1/m)*np.dot(X.T,dZ1)
                  db1=(1/m)*np.sum(dZ1,axis=0)
                  return dW1,db1,dW2,db2
              def update_weights(self,dW1,db1,dW2,db2):
                  self.W1-=self.learning_rate*dW1
                  self.b1-=self.learning rate*db1
                  self.W2-=self.learning rate*dW2
                  self.b2=self.learning rate*db2
              def cross entropy loss(self,X,y):
                  _,_,_,y_pred=self.forward_pass(X)
                  entropy=np.where(y==1,np.log(y_pred.flatten()),np.log(1-y_pred.flatten())
                  return -np.sum(entropy)
              def predict(self, X):
                  output=self.forward pass(X)[3].flatten()
                  predictions = (output > 0.5).astype(int)
                  return predictions
              def accuracy(self, X,y true):
                  y_pred=self.predict(X)
                  return np.mean(y_true == y_pred)
              def train(self,X,y):
                  for epoch in np.arange(self.epochs):
                      if self.cross_entropy_loss(X_val,y_val)<self.tol:</pre>
                      permutation = np.random.permutation(X train.shape[0])
                      X train shuffled = X train[permutation]
                      y_train_shuffled = y_train[permutation]
                      for i in range(0, X_train.shape[0], self.batch_size):
                          X batch = X train shuffled[i:i + self.batch size]
                          y_batch = y_train_shuffled[i:i + self.batch_size]
                          Z1, A1, Z2, A2 = self.forward pass(X batch)
                          dW1, db1, dW2, db2 = self.backward prop(X batch, y batch, Z1,A1,
                          self.update weights(dW1, db1, dW2, db2)
In [35]:
          model=TwoLayerPerceptron(2,10,1)
In [36]:
          model.train(X_train,y_train)
         <ipython-input-34-283db22abf63>:56: RuntimeWarning: divide by zero encountered i
           entropy=np.where(y==1,np.log(y_pred.flatten()),np.log(1-y_pred.flatten()))
In [37]:
          model.accuracy(X test,y test)
```